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MULTIRESOLUTION ANALYSIS AND IMPLEMENTATION OF GRAPE SPECIES CLASSIFICATION USING NEURAL NETWORK

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ABSTRACT

In the field of agriculture the species plays an important role for precision growth; therefore it is necessary to study species of plant using newest technology available in the literature. Before studying species it is very important to recognition the botanical species correctly so, in this paper we employ Pattern Recognition Neural Network (PRNN) and image Texture analysis based algorithm to develop a system for Grape plant species classification. Here 12 different features are extracted using Discreet Wavelet transform and are normalized into 4 principal variables which consists the input vector of the PRNN. The PRNN is trained om database of 220 leaf images collected for different fields to classify 4 kinds of species like viz Clone, Manik, Sonaka and Thomson. Accuracy greater than 80% is achieved for trained images and results are validated with the field result which shows value to our method. As no other research are found on species classification so, this algorithm can be considered as a novel approach for species classification, our algorithm is an accurate artificial intelligence approach which is fast in execution and easy in implementation and use.

KEYWORDS: Texture Analysis, Pattern Reconition Neural Network, Wavelet Filters, Multiresolution Analysis, Grape Plant

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Original Article

1 INTRODUCTION

Texture refers to properties that represent the surface or structure of an object (in reflective or transmissive image, respectively); it is widely used, and perhaps intuitively obvious, but has no precise definition due to its wide variability [1]. One can define texture as a something consisting of mutually related elements; therefore humans are considering a group of pixels (a texture primitive or texture element) and the texture described is highly dependent on the number considered(the texture scale)[2]. But the same cannot be true with the visually same textures. The machine vision system will not able define or describe the texture which are same visually but differs in its scale some of this images[3].

The Study of texture analysis for Grape Plant Species Classification system reveals that the Shape, Color and global texture of all grapes leafs of species remains relatively same that is visually same but the local texture of individual specie varies[4]. So to find texture feature which can well describe texture of visually same but differs in local texture, also the texture feature which are invariant for Scale, Illumination and Rotation are discussed [5].

Texture consists of texture primitives or texture elements, sometimes called texels. Texture description is scale dependent. The main aim of texture analysis is texture recognition and texture-based shape analysis [6]. People usually describe texture as fine, coarse, grained, and smooth. In this paper we discussing some of the

important ways by which this problem can be accomplished and concluding with best texture feature or a combination of feature that can able to discernment the similar textures of different scales using Neural Network [7]. Section 1describes the introduction to study and algorithm, section 2 continues with the basics theory and model of texture analysis using Wavelet analysis. Section 3 introduces the concept algorithm details and Methodology. Section 4 describes different Experimental results obtained on collected database. In Section 5 the results and study is discussed and finally the paper is concluded in section 6.

II. BASIC THEORY

A. Wavelet Analysis

The analysis of a non-stationary signal using the FT or the STFT does not give satisfactory results. Better results can be obtained using wavelet analysis. One advantage of wavelet analysis is the ability to perform local analysis [8-9]. Wavelet analysis is able to reveal signal aspects that other analysis techniques miss, such as trends, breakdown points, discontinuities, etc. In comparison to the STFT, wavelet analysis makes it possible to perform a multiresolution analysis. The general idea of multiresolution analysis will be discussed in A. The wavelet functions and their properties are the subject of B. The continuous wavelet transform (CWT) will be treated in C together with the discretized version of the CWT.

B. Multiresolution Analysis

The time-frequency resolution problem is caused by the Heisenberg uncertainty principle and exists regardless of the used analysis technique. For the STFT, a fixed time-frequency resolution is used. By using an approach called multiresolution analysis (MRA) it is possible to analyse a signal at different frequencies with different resolutions [10]. The change in resolution is schematically displayed in Figure 1.

For the resolution of Figure 1 it is assumed that low frequencies last for the entire duration of the signal, whereas high frequencies appear from time to time as short burst. This is often the case in practical applications.

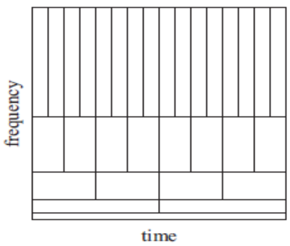


Figure 1: Multiresolution Time-Frequency Plane

The wavelet analysis calculates the correlation between the signal under consideration and a wavelet function ψ (t). The similarity between the signal and the analyzing wavelet function is computed separately for different time intervals, resulting in a two dimensional representation. The analyzing wavelet function ψ (t) is also referred to as the mother wavelet [11].

1. A wavelet must have finite energy

$$E = \int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \tag{1}$$

The energy E equals the integrated squared magnitude of the analysing function ψ (t) and must be less than infinity.

2. If ψ (f) is the Fourier transform of the wavelet ψ (t), the following condition must hold

$$C_\psi = \int_0^\infty \frac{|\hat{\Psi}(f)|^2}{f} df < \infty \quad (2)$$

This condition implies that the wavelet has no zero frequency component (ψ (0) = 0), i.e. the mean of the wavelet ψ (t) must equal zero. This condition is known as the admissibility constant. The value of C_ψ depends on the chosen wavelet.

3. For complex wavelets the Fourier transform ψ (f) must be both real and vanish for negative frequencies [12].

C. Multiresolution Filter Banks

For high frequencies (low scales), which last a short period of time, a good time resolution is desired. For low frequencies (high scales) a good frequency resolution is more important. The CWT has a time-frequency resolution as shown in Figure 2. This multiresolution can also be obtained using filter banks, resulting in the discrete wavelet transform (DWT). Note that the discretized version of the CWT is not equal to the DWT; the DWT uses filter banks, whereas the discretized CWT uses discretized versions of the scale and dilatation axes [13]. The low-pass and high-pass filtering branches of the filter bank retrieve respectively the approximations and details of the signal x (k). In Figure 3, a three level filter bank is shown. The filter bank can be expanded to an arbitrary level, depending on the desired resolution. The coefficients $c_l(k)$ (see Figure 3) represent the lowest half of the frequencies in x(k), down sampling doubles the frequency resolution. The time resolution is halved, i.e. only half the numbers of samples are present in c_l (k).

Figure 1 is similar to the resolution shown in Figure 3. For a special set of filters L(z) and H(z) this structure is called the DWT, the filters are called wavelet filters

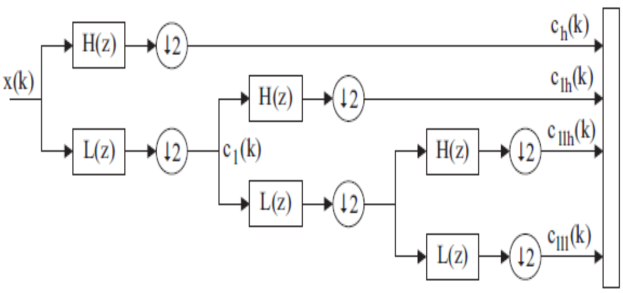


Figure 3: Three Level Filter Bank

D. Neural Network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems [14]. As in nature, the connections between elements largely determine the network function. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output [15]. Wavelet analysis has attracted much attention recently in Image analysis. It has been successfully applied in many applications such as image analysis, classification system and other texture analysis applications. Wavelet Packet

Decomposition algorithm is used for feature extraction. Dabuencheis order-2 wavelet family is used here and feature vector coefficients are obtained at 2^{nd} level. Then features like Entropy, Mean, Standard Deviation and Variance is calculated for all decomposition of image like Horizontal, Vertical and Diagonal.

III. METHODOLOGY

A. Flowchart

As Shown in flow chart the algorithm steps are followed and system is developed for Grape plant leaf species identification. First leaf images are captured under free environment from different farms near Sholapur district and Database is collected of 220 images. Then DWT using Dabuencheis wavelet of order 2 and at level 2 is applied and features are extracted. Patten Recognition Neural Network is used for classification purpose and results are obtained.

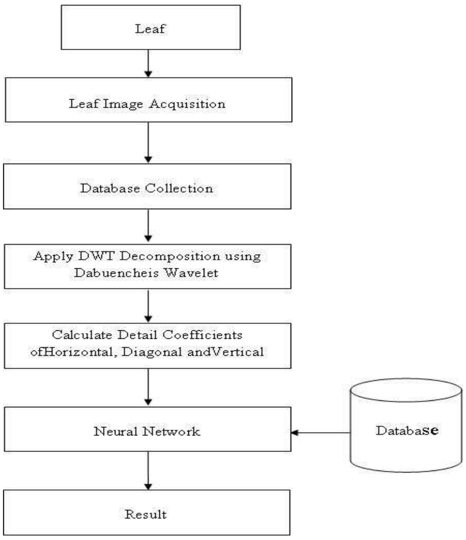


Figure 4: DWT Implementation Flow Chart

B. DWT Features Extraction

The leaf image is first decomposed with two levels DWT decomposition using Dabuencheis wavelet then features like Entropy, Mean, Standard Deviation and Variance is estimated for all decomposition of image like Horizontal, Vertical and Diagonal here in paper only horizontal decomposition is considered and discussed.

The extracted features H_Entropy, H_Mean, H_Standard Deviation, and H_Variance from horizontal decomposed plane are shows the prominent and best features to describe leaf image from different plots and regions. The graphs for the respective parameters for all four species for the database are as shown in figure 5 to 8.

1. Entropy

The Entropy measures amount of information in any signal or image here Figure 6 entropy for all species is plotted. The value of entropy doesn't vary more for a species clone and manik and gives discriminate feature value for all species. As it provides a better intercorrelation

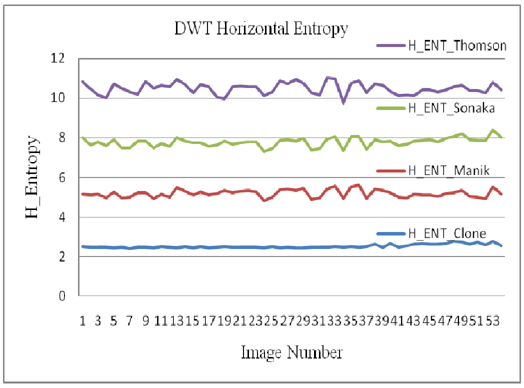


Figure 5: DWT Horizontal Entropy for all Species

2. Mean

The Mean is the mean of any signal or image here Figure 7 mean for all species is plotted. -The value of Mean vary more for a species itself like clone and manik same with others. So, it cannot be used for classifier as it cannot discriminate mean value of each species.

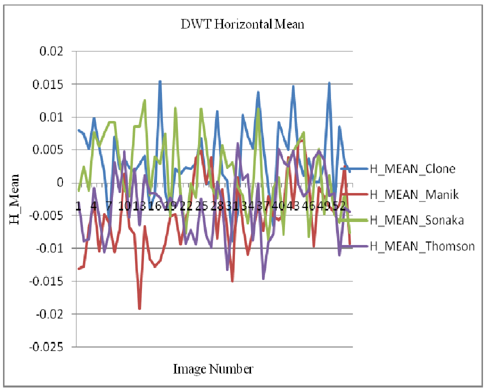


Figure 6: DWT Horizontal Mean Features for all Species

3. Standard Deviation

Standard Deviation is square root of variance which reflects how the image change indepdently without considering any mean or sigma values for calculating distribution. The values of species are as shown in above Figure 8 for all species. As Standard Deviation gives good discriminations for all species so we can use it for classification.

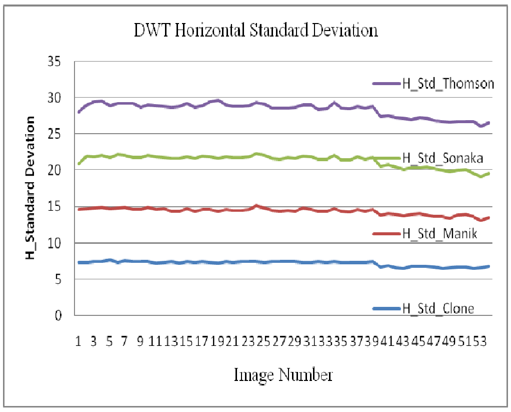


Figure 7: DWT Horizontal Standard Deviation for all Species

4. Variance

Variance is an unbiased estimator of the variations of the population from which X is drawn, as long as X consists of independent, identically distributed samples. Variance for all species is as plotted in figure 9. As the feature variance gives the changes between all species so it can be used for classification.

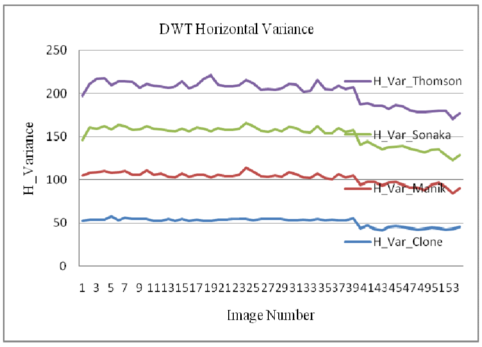


Figure 8: DWT Horizontal Variance for all Species

Figure 9 and Figure 10 shows the decomposition of image at level three which gives approximation and details of leaf image. This decomposition is carried out using a Wavelet Analysis Tool available in MATLAB. As discussed above the features extracted using DWT out of which some feature gives good co-relation and some varies drastically, so they cannot be used for classification. The features which are not co-related are the Mean of Vertical, Horizontal and Diagonal. The mean is measure of mean value in an image as all the leafs are nearly of same color and shape. Hence the mean value cannot be considered as distinguishing feature. If mean is used in classifier it can be reason in reduction of accuracy of classifier.

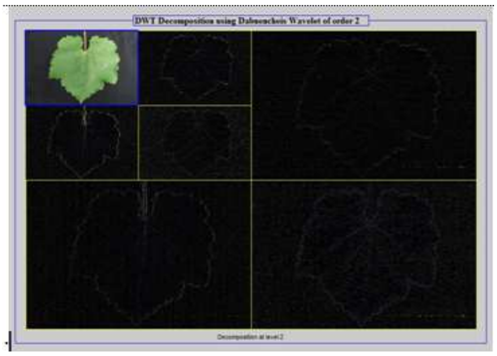


Figure 9: Wavelet Decomposition

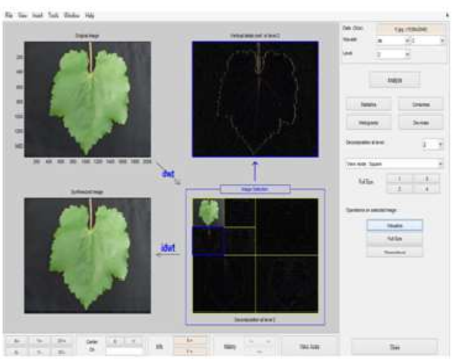


Figure 10: 2-Level Decomposition

C. Classification Using Pattern Recognition Neural network

The features obtained using DWT are used with Neural Network. For implementation of classifier Pattern Recognition Neural Network is used and the algorithm is implemented using nprtool available in matlab. The Configuration of neural network used for developing the algorithm is as follows.

- Number of Input Features:-5
- Number of Output Classes:- 4
- Number Of Hidden layer Neurons:-10
- Data Division:- Random and Min Max mapping
- Training Algorithm:- Scaled Conjugate Gradient
- Performance Analyses: - Cross-Entropy.
- Maximum Epochs:-1000

Using above settings and configuration the training result is as shown in figures below.

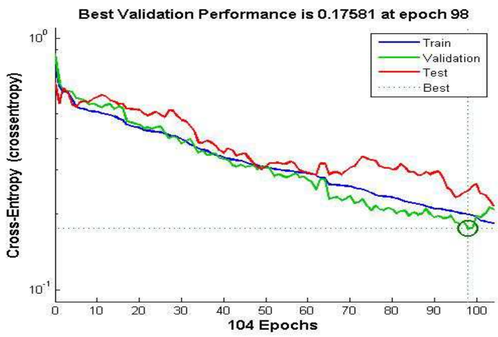
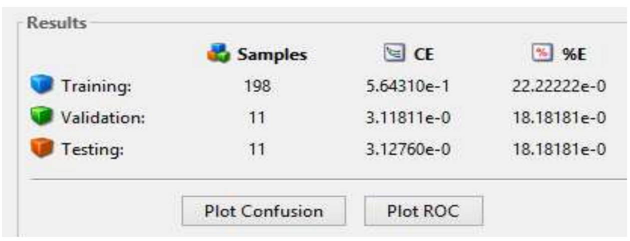


Figure 11: Neural Network Performance

As number of epochs set to 1000 but minimum error and Best validation is achieved at epoch 98 only. Trained neural network provides performance and confusion matrix are as shown Figure 11, Figure 12 and Figure 13. The best validation for training is achieved on epoch number 98 the Cross-Entropy at epoch 98 is 0.17581. The achieved Percentage Error and Cross-Entropy as discussed in experimental results.

IV. EXPERMENTAL RESULTS

A. Cross-Entropy and Percentage Error


Results

	Samples	CE	%E
Training:	198	5.64310e-1	22.22222e-0
Validation:	11	3.11811e-0	18.18181e-0
Testing:	11	3.12760e-0	18.18181e-0

Figure 12: Cross-Entropy and Percentage Error

The Cross-Entropy and Percentage Error for Neural network is shown for all Training, Testing and Validation.

Where 11 to 17 images randomly selected for Validation and Testing and remaining images are trained. Then the results are conformed using confusion matrix. The confusion matrix for trained neural network is as follows.

Training Confusion Matrix

Confusion matrix displays classification confusion states and it also shows the relative classification of classes as shown in figure 13

In training confusion matrix 33 out of 55images of clone species class is used.

- While training 27 classified as Clone class.
- 6 images of clone is misclassified as Manik
- resulting in accuracy of 81.1 %

Figure 13: Confusion Matrix for Trained Neural Network

In training confusion matrix 39 out of 55images of Sonaka class is used.

- 2 images of Sonaka are misclassified as Thomson.
- resulting in accuracy of 84.6 %

In training confusion matrix 41 out of 55 images of Manik class is used.

- While training 34 classified as Manik itself class.
- 6 images of Sonaka are misclassified as clone.
- 1 image is classified as a Thomson.
- Resulting in accuracy of 82.9%

In training confusion matrix 36 out of 55 images of Thomson class is used.

- While training 36 classified as Thomson itself class.
- 5 images of Thomson are misclassified as Sonaka.

- Resulting in accuracy of 87.8 %

The confusion matrix for Validation and Testing are as show in figure 13 for validation 90.9 % accuracy is achieved where as for test it reduced to 75.8% resulting in 15% reduction in accuracy with respect to validation and 9% with training.

DISCUSSIONS

In total, 220 plant images with uniform background including individual classes of Clone, Sonaka, Thomson and Manik species were classified. The performance of classifier is defined by the feature used to train the network as here features obtained gives better interspecies correlation, all the algorithms performed better on the dataset created as described in section 3, showing the value of our method of leaf texture extraction and classification. The result for the experiment is given in figure 13, 14 and 15 which show accuracy of algorithm for different methods with neural network in terms of percentage.

The developed algorithm is trained and applied on collected database. Figure 14 show accuracy of DWT features with neural network, For Neural Network number of images considered for training are as 33, 39, 41, and 41 for Clone, Sonaka, Manik and Thomson respectively. For testing purpose algorithm is applied on the leaf images which are not considered for training the Neural Network Figure 15 show accuracy of neural network for testing.

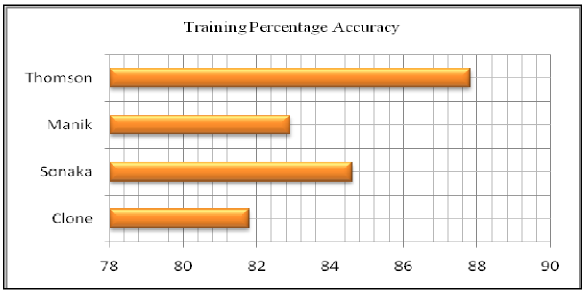


Figure 14: Training Percentage Accuracy of DWT Features NN

For testing Neural Network number of images considered for testing are as 17, 17, 15, and 17 for Clone, Sonaka, Manik and Thomson respectively. The neural network provides overall good accuracy, but accuracy of NN is reduced in case Sonaka species.

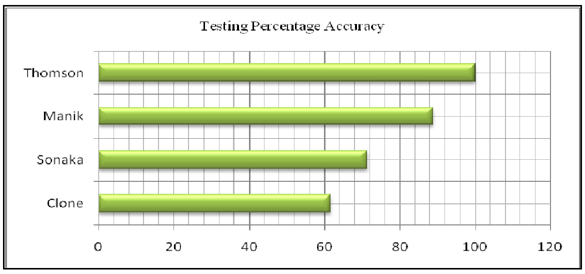


Figure 15: Percentage Accuracy of DWT Features for NN

CONCLUSIONS

Texture feature analysis and extraction has been investigated and largely applied from past few decades but, identifying the local texture of same color and shape is still challenging. The purposed algorithm of features extraction

using DWT with Dabuencheis wavelet of order 2 and of level 2 can be useful for identifying and analyzing local texture thus solving problem of local texture analysis by providing good correlation features values. An intelligent computer vision application has been developed to adapt over time for precision agriculture and to improve study of species in botanical field.

We have implemented a new approach for species classification using DWT and Wavelet. The results validate our classification system on the agriculture field and demonstrated its excellent generalization ability to classify species of Grape plant. In this work, the local texture analysis is learned and species are classified using Neural network, but the more information on local texture analysis can be obtained using combining different color texture analysis techniques and applying different classifiers which may produce a more powerful system for species classification.

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